Understanding Climate Sensitivity of Bioeconomic Systems: A Structural Approach to Adaptive Commercial Fishing Behavior and Fishery Networks

Job Market Paper

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Abstract

As climate change reconfigures ocean ecosystems, there is an urgency to develop a more complete understanding of the responses of commercial fishers reliant on those ecosystems and the resilience of the fishery and fishing communities. Research to date has demonstrated that fishers use diversification strategies to mitigate risk associated with both long-run climate change and short-run climate shocks. Individual adaptive fishing decisions impact other vessels in the region, interact with the marine ecosystem, and shape macroscopic decision-making conditions, constituting a complex human and natural system. While network theory provides a useful framework for representing harvest, competition, and interdependence among agents in complex systems, the economic foundations that explain the network topology and climate resilience of commercial fishing communities are not fully understood. I develop a structural Random Utility Model that is calibrated to fish landings data to describe individual fishing choices throughout the year, whose collective decisions determine the network topology. I map the inputs to decision making to individual vessels' fishery diversification behavior and in turn to network outcomes, showing that network structures can depict complex adaptive fishing behavior. This research connects the micro-foundations of individual decisions with the macro behavior of networks to improve our understanding of resilience and equity in commercial fishery systems.

Introduction

Ocean warming is causing changes in ocean circulation and stratification, losses in oxygen concentration, and shifts in primary productivity (Free et al., 2019). Together, these changes are decreasing ocean productivity, altering food web dynamics, reducing species abundance, shifting species ranges (Hoegh-Guldberg and Bruno, 2010), and changing commercial fishing behavior (Pinsky et al., 2021). Climate change is also increasing the frequency, intensity, and duration of short-term climate shocks (Di Lorenzo and Mantua, 2016) that cause an increasing number of fishery failures (Bellquist et al., 2021). As climate change reconfigures ocean ecosystems (Wernberg et al., 2016), there is an urgency to develop a more complete understanding of the responses of commercial fishers dependent on those ecosystems and the resilience of the fishery and fishing communities.

Research to date has demonstrated that fishers use diversification strategies to mitigate risk associated with both long-run climate change and short-run climate shocks (Anderson et al., 2017). For example, market squid fishers in Southern California—particularly those operating larger vessels—can adapt to slowly changing squid stock distributions by shifting their geographic range of fishing. On the other hand, Powell et al. (2022) have shown that fishers who are older and more experienced are less likely to alter their behavior to include fisheries. Short-run climate shocks, which are expected to increase with climate change, can also be mediated through adaptive fishing behavior. In response to the short-run 2015-16 Harmful Algal Bloom that precipitated closures of the West Coast Dungeness crab fishery, Fisher et al. (2021) found a significant reduction in fishing activity, spillover of fishing effort from the Dungeness crab fishery into other fisheries, and spatial variation in the network of fishery participation following the climate shock. At the same time as the oceans are experiencing unprecedented changes, commercial fishers in the US West Coast and Alaska have exhibited a decline in fishery diversification since the mid-1980's (Kasperski and Holland, 2013).

A network approach is effective for understanding effort allocation between fisheries, which is the basis of fishery diversification (Addicott et al., 2019; Kroetz et al., 2019; Fisher et al., 2021; Fuller et al., 2017; Fisher et al., 2026). A typical fishery network describes the relationships between component nodes (fisheries, vessels) by their relative distance: the effect of one node on another diminishes with their separation in the network (Montoya et al., 2006). Network theory provides a framework to study not only the pairwise connections in a complex system (Mahon et al., 2008), but also higher order interactions (Battiston et al., 2020; Grilli et al., 2017). The pairwise and higher order relationships between fisheries can be used to infer diversification in fishing opportunities and make predictions about how changes to fish stocks, ocean conditions, or policies in one fishery will have spillover effects on other fisheries.

Understanding fishing resilience necessitates studying fishery systems as a whole since fishers and fisheries are connected through fishing effort diversification, shared reliance on fish stocks and port resources, competition and cooperation between fishers, and ecosystem functions. Optimal harvest and management of a fishery can be described with a dynamic bio-economic model (Gordon, 1954; Schaefer, 1957) and the interactions between fishers and fish in a constant environment can tend towards a stable state or cycle (Holling, 1973). Vessel operators' diversification decisions link otherwise unconnected fisheries, creating new non-linear dynamics of a complex system with the potential for multiple steady states (Strogatz, 2001; Gunderson and Pritchard, 2012; Hare and Mantua, 2000; Mahon et al., 2008). The environment of commercial fishing is non-constant: fishing communities are subject to fish demand, labor supply, input costs, and fishery policies and marine ecosystems are subject to long-run climate change and short-run climate shocks. The gradual shifts to components of the system alter its ability to withstand catastrophic events (Scheffer et al., 2001) and the interactions depicted in network theory capture the heterogeneity of components and their connectivity (Cohen et al., 2000; Scheffer et al., 2012; Newman, 2003; Gunderson and Pritchard, 2012).

Regional fishing communities are a complex social-ecological system (Fisher et al., 2026), for which network analysis is a powerful tool, specifically to describe its stability to perturbations. Graph theory has been used more widely in complex human and natural systems, for instance to study invasive species (Drake et al., 2017; Ashander et al., 2022), hydrological systems under anthropogenic activity (Wang et al., 2023), and wolf and prey dynamics in forestry settings (Courbin et al., 2014).

While the prior literature in fishery economics has demonstrated how shocks to a fishery can lead to spillover using network analysis (Addicott et al., 2019; Kroetz et al., 2019), there is little work mapping how changes in network topology translate into measures of the resilience or "capacity of a system to absorb stresses and continue functioning" (Levin and Lubchenco, 2008). Walker et al. (2004) states that resilience is a combination of the size of a shock from which a system can recover, the ease of changing the system, how close a current state is to a threshold, and how it is influenced by outside forces. Resilience, along with the capacity of the actors and the capacity for a fundamentally new system, determine its future trajectory. Complex systems have differing levels of resilience (Liu et al., 2007), and the study of resilience can help to reconcile the paradox of short term efficient use of resources and long term sustainability (Gunderson and Pritchard, 2012). Wilson et al. (2018) and Levin and Lubchenco (2008) define the resilience of a system as related to its ability to adapt to new stressors and keep functioning. Holling (1973) suggests that a complex system may have zero, one, or multiple different domains of attractions (elsewhere referred to as regimes), each with its own steady state. Hare and Mantua (2000) identifies three regimes in the North Pacific fishing system—1965-1976, 1977-1988, and 1989-1997—each defined by unique combinations of weather conditions and fish population dynamics and each with different implications for management decisions. Oceanic regime shifts cannot be fully explained without considering commercial fishing behavior and a thorough understanding of resilience can aid in climate-ready fisheries management and in supporting coastal communities(Litzow et al., 2014). While regime changes are largely unpredictable (Barnosky et al., 2012), Kroetz et al. (2019) use economic connectivity as a proxy for resilience, and Fuller et al. (2017) use network measures to gain information on potential changes to resilience over time. Network theory is a promising tool for measuring and understanding resilience in complex systems such as fisheries; however, the economic foundations that explain network topology and system resilience to climate shocks are poorly understood.

The proposed research contributes to the study of complex systems, fishery science, economics, and policy by connecting the microfoundations of individual fishing decisions with the macro behavior of networks to improve our understanding of resilience and equity in commercial fishery systems. Powell et al. (2022) and Fisher et al. (2021) demonstrate how fisher behavior responds to climate change and climate shocks. Jardine et al. (2020) takes a fleet-wide approach to responses to the Dungeness crab closures to understand inequality in economic impacts from climate shocks. Fisher et al. (2026) construct a qualitative network to trace how the unintended consequences of climate-adaptive behaviors among commercial fishers on community well-being. Using networks of fishing effort, this paper determines both individual fisher and network responses to changes in fishing conditions. In doing so, I further our understanding of the cross-scale interactions in complex systems: between individual-level fishing decisions and the macroscopic system dynamics. This will contribute to the growing body of literature on climate-ready fisheries (Wilson et al., 2018).

I achieve this contribution through an in-depth investigation of a focused set of network measures. My analysis is grouped into three questions. First, how do vessels respond to changes in input parameters? Second, how do input parameters shape network structures, and third, how can we relate vessel behavior and network outcomes, and under what conditions can we apply these findings to an empirical setting? I use simulated and empirical fishing decisions to question how adaptive behavior is depicted in network measures

and to generate testable hypotheses about how network structure shapes system resilience. As network theory becomes more prevalent in the field of fisheries economics, this set of analysis provides insight into the mechanisms by which networks take shape, creating the groundwork to use network theory to study spillovers and resilience in commercial fishing systems.

I define networks of fishery nodes in which two fishery nodes are connected if vessels participate in both fisheries. The network architecture of nodes and edges is related the stability of the system, and is impacted by the adaptive behavior found in the network (Valdovinos et al., 2016; Okuyama and Holland, 2008). The edge between two connected fishery nodes takes the weight of the number of vessels that participate in both fisheries. When fishing vessels diversify their fishing participation, they contribute to more edges with greater weights—finding higher edge weights would suggest that more fishers are participating in multiple fisheries. Greater diversification implies available adaptive behaviors when experiencing an external shock to a fishery node. More broadly, the impact of the loss of access or profitability of one fishery node on the network will be propagated through vessels' adaptive strategies. Average edge weight in a system provides information on the average connection between fishery pairs, and the capacity for spillovers through fishing effort (Addicott et al., 2019; Kroetz et al., 2019).

I also measure modularity, a measure of the quality of partitions found in the network (Fisher et al., 2021; Fuller et al., 2017). Higher modularity can indicate that vessel operators are constrained in their options (Stoll et al., 2016) or that unfavorable perturbations will be constrained to the module in which they occur (Earn et al., 2000). Whereas edge weights might generally suggest resistance to change and sudden transitions, modularity can indicate adaptive behavior that allows for gradual changes (Scheffer et al., 2012). Much of the theory developed on network measures is done in ecological settings that can be described by ordinary differential equations or have explicitly defined intertemporal dynamics. Generally, social networks differ from biological networks (Newman and Park, 2003) and specifically, it is unclear if ecological interpretations can be applied in the commercial fishery setting. The fisheries economics literature uses network connectivity, weights, and modularity to describe vulnerability to climate change without a full understanding of the mechanisms through which these metrics respond to changes in individual behavior or of their implications for system stability.

The simulated discrete choices are the outputs of a structural Random Utility Models (RUM) of fisher decision-making that I use to map microfoundations to fishing decisions to network measures. RUMs have been used in the fishery science and economics literature to describe vessel location choice (Holland and Sutinen, 1999, 2000; Abbott and Wilen, 2011) including alongside biological models (Smith and Wilen, 2003) and incorporating state-dependence (Smith, 2005). Recent work has used RUMs to describe the inputs to fishers' fishery decisions between specific choice sets (Stafford, 2018; Caballero et al., 2023; Reimer et al., 2022), and the research in this paper will extend this to the full set of fishery choices. I simulate a RUM model calibrated to commercial fish landings data in California from 2017-2021 as a means to measure how changes to inputs of fishing decisions aggregate across individuals. For instance, when costs increase, how do fishing vessels change their fishing strategies? Do they participate in fewer fisheries or do they continue to be as diversified in their participation but in a different set of fisheries?

The simulated fishing data supplements observed commercial fishing behavior in California. In commercial fishing, vessels are heterogeneous in the behavior, specializing in different fisheries based on preferences, knowledge, communication, and other unobservable characteristics (Smith, 2005). Furthermore, over time, regional vessels alter their fishing behavior in response to climate and policy changes (Oke et al., 2020). I use variation in empirically observed commercial fishing behavior over time and space to find patterns in the relationships between diversification and network outcomes. In supplementing the empirical data with

simulated data, I am able to exploit common causes of diversification and network measures. Both diversification and network measures respond to model input parameters, and the response of higher order network measures are mediated through diversification behavior and lower order network structural measures.

I find that fishing diversification responds monotonically to higher input costs: when switching and fishing costs increase, vessels diversify less. I observe simulated vessels' to respond to higher costs by both choosing to participate in fewer fisheries or choosing a more common fishery strategy: not only are fishing vessels less diverse, but as a fleet their set of strategies reduces to a few dominant strategies. Some network measures—like mean weight—consistently capturing the differences between the impacts of the two diversification responses on the network. Other measures—like modularity—are informative to system resilience but the response is nuanced. Commercial fishery networks can experience changes to underlying environmental, economic, or policy conditions that can have the same impact on diversification behavior while varying in the impacts on network topology. Depending on the connectivity of the setting, changes in the diversification of vessel fishery participation could decrease or increase modularity. Network measures provide insight into how changes in diversification can change system resilience to future shocks, but these shifts are most reliably interpreted in response to small changes of decision-making conditions.

There is wide support in the literature for regime shifts in the North Pacific (Hare and Mantua, 2000) and Litzow et al. (2014) find that those shifts cannot be understood without considering commercial fishing activity. I extend this study of marine system regimes, finding that the relationships between individual vessels' fishing behavior and collective system structure vary across both time and space. Across regimes, the same behavioral response can bring about an entirely different network response; within a regime, changes in diversification behavior are consistently correlated with a common change in network topology. Using empirical data, I show that a policy-maker can use recent behavior and topology to detect the regime in which a current region belongs. California regions belong to different regimes and pass through different regimes over time. The structural model reveals that in system states defined by higher fishing costs, more diversification can increase the potential for few strong spillovers; in states of lower fishing costs, more diversification can increase the potential for more fisheries and vessels to experience spillovers.

In the following methods section, I describe the structural fishery discrete choice model, vessels' diversification decisions, the fishery network construction, and the computation of the network measures as applied in the commercial fishery setting. I then provide my results. First, I describe the correlations between types of adaptive fishing behavior and network topology observed in California commercial fish landings from 2001-2021. Second, I turn to the simulation data to create a fuller understanding of vessel behavior and network responses to input conditions and I relate fishery diversification to network measures. Third, I demonstrate the identification of unique network regimes in the empirical and simulated data. I conclude with a discussion of the implications of my findings, focusing on their relevance for interpreting climate resilience, their limitations, and opportunities for future research.

Methods

I use the California fish landings data from the California Department of Fish and Wildlife. All fish caught under a commercial license must be documented with the state when vessel operators land their catch with local fish processors or sell under their retail license (PacFIN: http:// pacfin.psmfc.org/). This comprehensive data set of fishing activity includes the weight and ex-vessel revenue of all landed fish, along with species, vessel type, gear, and landing location. I complement the empirical fishing data with a simulated model of sequential myopic decisions calibrated to the empirical landings data. Each vessel has a size and home region (distributed as in the empirical setting) and in a given week chooses both a fishery and the region in which to fish and land their catch. I call their weekly decision a region-fishery—port and region map in Figure SI.1.

For example, a 20-foot vessel in San Francisco chooses between region-fisheries that include Central Coast Dungeness Crab, San Francisco Dungeness Crab, and Bodega Open Access Groundfish. I depart from the literature by including the region modifier in order to expand the set of available choices to yield a larger meta-network. Prediction accuracy increases with network size (Berlow et al., 2009) and network measures are more robust in larger networks.[1] I assume that fishers start at their home port at the beginning of each week and choose the region-fishery that maximizes their expected utility.

The Random Utility Model

In each week, vessels face expected revenue and fishing costs for each fishery—defined as a combination of fish, gear, vessel type, and permitting. In week t, fishing vessel i chooses to participate in the fishery j that offers the greatest indirect utility (approximated in dollars), and earns that expected utility as revenue,

$$\begin{aligned} U_{ift} &= V_{ift} + \varepsilon_{ift} \\ &= \mathbf{T}_f ExpRev_{ft} - \alpha FishingCosts_{if} - \beta SwitchingCosts_{fz^{-1}} + \varepsilon_{ift} \\ z_{it} = f \iff & U_{ift} > U_{ijt} \; \forall \; f \neq j, \end{aligned}$$

in which V_{ift} and ε_{ift} denote the observed and unobserved components (to the researcher) of indirect utility, respectively. I model indirect utility as a function of the expected revenue $ExpRev_{ift}$, a time-invariant fishery participation cost $FishingCosts_{if}$, and a state-dependent switching cost (Smith, 2005; Caballero et al., 2023), $SwitchingCosts_{fz^{-1}}$, that represents the cost of switching to fishery f given that fishery z was chosen in the previous period $t-1$. $\mathbf{T_f}$ is a weekly-updated stock-effect vector by fishery that introduces competition, limiting catch per unit effort for region-fisheries that have been heavily fished in prior weeks. Vessel-level state dependency is introduced through the costs to switch between fisheries in consecutive weeks, and fleet-level path dependency is found in the fish stock effect. α, and β are unique cost scalars that provide variation between simulations—both single value constants for all i, f, t.

The remaining component of indirect utility, ε_{ift}, represents a fisher's decision factor that captures other considerations influencing a fisher's choice that is unobserved by the researcher. Aligned with multinomial logit specification, ε_{ift} are independently and identically Gumbel distributed with scale parameter $\lambda_{ift}[0,1]$, a type one extreme value (T1EV) (Train, 2009; Stafford, 2018). Which is to say across vessels that the unobserved utility for a each fishery-week-vessel decision U_{ift} is independent of irrelevant alternatives $U_{\eta\phi\tau} \forall \; \eta \neq i, \; \phi \neq f, \; \tau \neq t$. Independence across vessels and fisheries allows for a vessel to have fishery information, preferences, or capital or labor comparative advantages that provide additional expected utility compared to the rest of the fleet. Across time, the TIEV error provides vessels an opportunity to participate in a fishery at a non-seasonal time, or otherwise make decisions outside of dominant seasonal strategies. However, this does not preclude the expected serial correlation in fishing decisions due to the imposed state-dependent switching costs.

Simulation Variables

The observed variables in the Random Utility Model are estimated from and calibrated to the fish landings from 2017-2021.[2] I choose the most recent landings data in order to exclude extreme exogenous climate shocks. The 2014-2016 Northeast Pacific marine heat wave had vast negative (and some positive) impacts on the California commercial fishing industry, including the closure of the Dungeness Crab fishery

[1] In this paper, the limitation is in modularity, as evident in the computation, found in the network measure methods. Briefly, in the summation across all pairwise combinations of nodes to compute modularity, a node in its own module is not counted (all pairwise combinations multiplied by a delta function evaluated as 0 when a node is not in the same module as the other node in the pair). This is explored in more detail in Fortunato (2010); Fortunato and Barthélemy (2007)

[2] figures to come

due to domoic acid contamination and the collapse of salmon due to overly optimistic model forecasts, low escapement, and low juvenile returns (Free et al., 2023).

I model expected revenues for a given vessel as information shared within all vessels of that class. Expected revenues vary by vessel size, region-fishery, and week, matching the scale of the RUM decisions. I assume vessel operators combine signals that include recent and historical landings data—from both their own and their region's past landings. Using the California landings data, I estimate expected revenue in reduced form following a Gordon-Schaefer production function (Gordon, 1954; Schaefer, 1957),

$$\log(R_{ijtf}) = \gamma_{yf} + \xi_{jf} \log(R_{tf}) + \varepsilon_{ijtf}$$
$$ER_{jtf} = \exp\big(\hat{\gamma}_{yf} + \hat{\xi}_{jf}\ \log(R_{tf}) + \varepsilon_{ijtf}\big)$$

in which R_{ijtf} is the total ex-vessel revenue earned by each vessel i (of size class j) in every week-year t and each region-fishery f and R_{tf} is the total ex-vessel revenue for each fishery f across all week-years t. The empirically observed intra-annual variation in landings introduces the fishery-specific seasonality reflective of fish population dynamics, weather, fishery season starts and duration, and fishing behavior. Vessel-level variation identifies $\hat{\beta}_{jf}$, an elasticity of vessel-class-fishery revenue to fleet wide fishery revenue and $\hat{\alpha}_{yf}$, a year-fishery fixed effect. The variation in β_{jf} by vessel-class and fishery reflects the suitability of each vessel-class for participating in each fishery due to the economies of catch revenue, vessel range, and operating costs. The year-fishery constant α_{yf} captures changes in catchability constant for all vessels across years due to temperature, fish migration, escapement, and recruitment, vessel risk-mitigation or fishing trends, and market demand. The option not to fish is available to all fishing vessels in each period, and is assumed to yield a revenue of 0.

The fishing costs represent the monthly fixed costs of owning, docking, and maintaining a vessel and gear suitable for each fishery, along with variable costs of labor and equipment. Vessel characteristics such as the length, horsepower, and tonnage present differential cost incentives for different types of fisheries. Similarly, vessels own and invest in fishery-specific gear and crew expertise. For each fishery and vessel class, fishing costs are time-invariant across all weeks in the simulation iteration. Together with expected revenue, fishing costs enforce seasonality: expected revenue varies with empirical landings throughout the year for each fishery and vessel-class, exceeding fishing costs only in the weeks in which there are landings for the vessel class, region, and fishery combination. In this way, the RUM parameter β on fishing costs ajdusts the length of the fishing seasons.

Fishing and switching costs are alternative-specific constants chosen to minimize the difference between observed and simulated region-fishery participation. I describe the full calculation and calibration procedures for fishing costs and switching costs in supplemental information. The decision not to fish yields no revenue and is subject to no costs and it is costless to switch from fishing to not fishing, or vice versa. The expected utility of not fishing for a given vessel at a given time is the unique type 1 extreme value draw.

Stock effects and switching costs introduce vessel and fleet level state-dependence. The stock effect imposes competition over time as it scales the catch per unit effort of expected revenue in a given week based on fishing activity up to that week. In week t, all vessels' expected revenue for a given region-fishery f diminishes if simulated participation outpaces empirical participation in weeks $[0, t-1]$. In this way, collective fleet decisions impact future individual decisions. A single vessel's participation in fishery f in weeks $[0, t-1]$ may not impact their expected utility in week t; however, the participation decisions of the fleet in aggregate will deter the less effective (vessels in a different switching cost state due to their choice in week $t-1$ or belonging to classes with lower expected revenue or higher fishing costs) vessels from participating in fishery f. I also impose switching costs of participating in fishery f given participation in fishery z in the previous

period. As a result of the calibration procedure, a fishery can have high switching costs for all fisheries if it is a restricted access fishery or has high permit costs. Additionally, fishery pairs can have high switching costs if the gear and vessel requirements are different or incompatible.

I use a bootstrap procedure to generate simulated fishing decisions in which unique fishing cost $\alpha \sim \text{Uniform}(0, 5)$ and switching cost $\beta \sim \text{Uniform}(0, 5)$ scalars—along with stochastic T1EV draws—produce a unique set of fishing decisions. An increase in fleet-wide fishing costs could be the result of an ecosystem-wide climate shock or industry-wide policy shock that reduces catch per unit effort or shortens the fishing season across all fisheries. It could also be the cause of a market shock on the demand for domestic fish or labor or capital costs. An increase in fleet-wide switching costs reflects a fleet-wide trend towards specialization in response to fewer open access fisheries and higher permit prices. The year of fishing decisions yields the data that composes a network. I repeat this for all n iterations in the bootstrap, yielding a panel of length n in which each cross-section contains the draw of cost scalars and the vessel diversification and network outcomes. Each simulation of 280 vessels across all California regions can choose to fish in 36 region-fisheries.

Quantifying Fishing Diversification Decisions

To describe the diversification outcome of a simulation-year, I use mean vessel diversification and the heterogeneity of fishery participation strategies in the fleet. These non-network measures provide a glimpse into the variations in individual vessel behavior and the breadth in vessel fleet decisions that together create heterogeneity across fishery networks. Vessel diversification is the mean number of fisheries per vessel across all vessels in the fleet in the simulation year. Vessel operators will choose to participate in more fisheries if more fisheries offer expected utilities in excess of costs. The only vessels whose fishing behavior contributes to the network are the diversified vessels (those participating in two or more fisheries).

Iterations are further distinguished by the overlap in the sets of chosen region-fisheries. The number of unique fishery participation strategies captures this variation. A vessel's fishery participation strategy is the set of fisheries in which they participate in a given simulated year at least once. The number of unique strategies is the sum of unique participation sets of two or more fisheries across the fleet. For example, the observed sets of fisheries $\{A, B\}$, $\{B, C\}$ and $\{A, B, C\}$ are three unique strategies, regardless of the number of vessels employing strategy $\{A, B\}$ or the number of weeks those vessels participate in fishery A.

Network Construction and Analysis

I describe annual simulation and empirical decisions with annual fishery-fishery networks in which edges between fishery pairs are weighted by the sum of vessels that participate in both fisheries in a a simulated or observed year (Addicott et al., 2019; Kroetz et al., 2019). In the empirical setting I use a vessel-week panel, in which each observed vessel is assigned the fishery for which they earned the most ex-vessel revenue, following the restriction in Caballero et al. (2023) of each vessel to a single fishery each week. The data that composes a network can be represented in a fishery-by-fishery adjacency matrix A, in which the ij^{th} element is the number of vessels that participate in both fishery i and fishery j. Element A_{ij} is equal to the number of vessels for which the set of fisheries $\{i, j\}$ is a subset of their fishery participation strategy (Figure 1). A vessel that uses strategy $\{i, j, h\}$ would increase the elements $\{ij, jh, ih\}$ by one. An edge exists when element $A_{ij} > 0$, and it takes the weight of A_{ij}. The network is symmetrical, and the network of edges requires only the upper or lower triangle.

In each empirical or simulated annual network, I analyze the network's largest connected component—the subset of fishery nodes in which every node has at least one edge to another in the subset (Figure 1). The fisheries that comprise the largest connected component can vary. A connected component represents the behavior among vessels that employ fishing strategies that are linked through shared participation across

at least one fishery. If the adjacency matrix were arranged by component membership it would be block diagonal, where each block represents a connected component. While there can be multiple connected components in any given empirical or simulated annual network, both node- and network-level measures are unreliable in describing the topology of a network of unconnected components (McNulty, 2022; Owen-Smith et al., 2020). Further, an analysis of the largest connected component benefits from containing the most nodes—the nodes with the most connections to other nodes (Vitali and Battiston, 2014; Cui et al., 2025; Sheykhali et al., 2020). In the case of commercial fishing communities, this subset of fishery nodes is likely to contain the most unique strategies and the behavior of the vessels interlinked by these strategies. Further, this connected component is the one most susceptible to spillovers from climate shocks and therefore critical for assessing climate resilience.

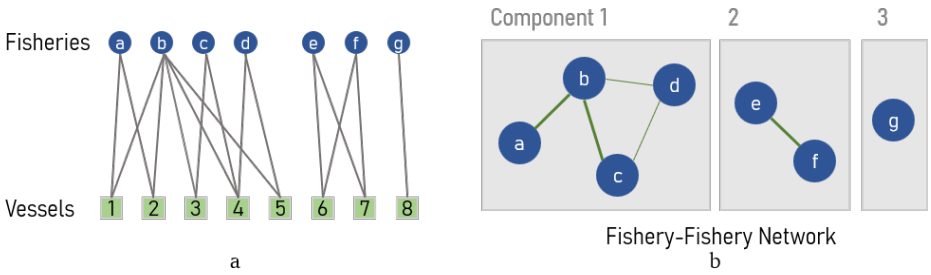

Figure 1: Network construction from fishing behavior. **(a)** Vessel (green squares) participation in fishery nodes (lines to blue circles). **(b)** Participation is projected into a fishery-fishery network, with green edges weighted by the number of vessels participating in the pair of fishery nodes. Component 1 of fisheries a, b, c, and d is the largest connected component with four nodes. Although not strictly necessary, the largest connected component most often reflects the behavior of the largest group of vessels (here vessels 1-5). Components 2 and 3 are smaller than component 1 and remain separate due to the lack of vessel diversification across their respective member fishery nodes.

I look at the fundamental properties of the co-participation network: the number of edges, the number of fishery nodes, and edge weight. The number of fishery nodes increases as the biggest group of fisheries interconnected by fishing behavior contains more fisheries. The number of edges and the edge weights increase as more vessels diversify. A non-diversified vessel participating in one fishery in the network contributes to neither the number of edges nor the edge weights. An increase in the number of edges or nodes could imply that there are more fisheries susceptible to spillovers from policy or climate shocks in another fishery in the network. Mean edge weight is the most general network measure of diversification. If a vessel chooses to diversify more, mean edge weight goes up, regardless of the vessel's choices of fishery. For example, if a vessel had been participating in fisheries $\{i, j\}$ and chooses to participate in fishery f, the sum of adjacency matrix A increases by 2 ($\{A_{if},\ A_{jf}\}$ each increase by 1), for any chosen fishery f.

Connectance (also referred to as connectedness) compares the ratio of observed edges to the number of possible edges, $C = \frac{\#\mathbf{observededges}}{\#\mathbf{possibleedges}} = \frac{\#\mathbf{edges}}{\mathbf{n(n-1)/2}}$ for n nodes. Connectance greater than 0.15 is high (Dunne et al., 2002), and connectance lower than $\frac{n-1}{n^2}$ would imply that the network is dissociated into sub-graphs that should be analyzed separately (Gilbert, 2009). Connectance is generally assumed to be positively correlated with protection from environmental threats: high connectance can be a characteristic of a system in which vessel operators would be protected from the impacts of fishery shocks (Dunne et al., 2002). However, a system with high connectance can be vulnerable if it has more specialists and fewer generalists: specialists face an increased risk of extinction while generalists can resist extinction (Heleno et al., 2012). While the removal of any fishery node would be expected to increase the vulnerability of fishing

vessels to future climate shocks, fishery closures can have uncertain effects on network connectance (Gilbert, 2009). Connectance will decrease when the removed fishery nodes are highly connected to other fishery nodes and increase when the removed fishery nodes are poorly connected. In complex systems, connectance responds nonlinearly to external climate shocks (Merz et al., 2023) and the nature of the response is highly context-specific due to variations in individual behavior (Heleno et al., 2012; Berlow et al., 2009).

Modularity refers to the compartmentalization of the system, where highly modular systems have densely connected communities loosely connected to other connected communities (Newman and Girvan, 2004); communities (modules) are evaluated with a clustering algorithm that maximizes modularity (Pons and Latapy, 2005; Fuller et al., 2017)). Modularity assesses the extent that weighted interactions in a network occur within modules rather than between modules, relative to a null model based on mean interactions in the network. In a weighted network, modularity takes a value from $[0, 1]$,

$$Q_w = \frac{1}{2m} \sum_{ij} \left[A_i j - \frac{k_i k_j}{2m} \right] \delta(\sigma_i, \sigma_j)$$

for the sum of edge weights in the network $m = \frac{1}{2} \sum_{ij} A_{ij}$ and the sum of edge weights attached to vertex i, $k_i = \sum_j A_{ij}$. $P_{ij} = \frac{k_i k_j}{2m}$ can be understood as the expected weight for the edge between nodes i, j in a counterfactual "null" model in which the edge weights of nodes i, j were uniformly distributed. Thus, $A_{ij} - P_{ij}$ measures the difference between the observed edge weight and what would be expected in the null model (Barber, 2007). The delta function $\delta(\cdot)$ is equal to one when nodes i and j are in the same module and zero otherwise. In the fisheries context, higher within-module connection occurs when the number of vessel co-participating in module-member fisheries i, j exceed the mean number of diversified vessels participating in fisheries i and j (i.e. vessels participating in fishery i and at least one fishery in $F \setminus i$). In a network with a module of single fishery node $f \in F$, $\delta(\sigma_f, \sigma_c) = 0 \ \forall \ c \in F$ and its edge weights do not contribute to the modularity for that network. This causes measurement error in small networks which have a greater likelihood of single-node modules. Assuming the presence of two or more clusters with two or more nodes in each, modularity increases as vessels divide into non-overlapping diversification strategies (Fortunato, 2010; Fortunato and Barthélemy, 2007). The fishery network modularity is high when the fleet strategies are well partitioned: two or more groups of vessels participating in non-overlapping fishery sets. Modularity decreases as the sets of fisheries overlap, until all vessels are participating in the same set of fisheries and $A_{ij} = P_{ij} \ \forall \ i, j \in F$.

I focus on the network measures of nodes, edges, connectance, edge weight, and modularity in for their prevalence in the literature and ease of interpretation. More nodes implies more fisheries may experience spillovers and there are more fisheries for which climate shocks can impact the system. Greater mean edge weights can be expected to predict a greater propensity for adaptive behaviors (Scheffer et al., 2012) and spillovers of climate or policy shocks across the system (Addicott et al., 2019). Modularity has an ambiguous relationship with resilience: increase modularity can reduce adaptive capacity if they constrain participants to certain strategies (Stoll et al., 2016) or increase it by buffering agents against unfavorable shocks (Earn et al., 2000). Scheffer et al. (2012) claim that modular networks tend to respond gradually to changing conditions.

Results

Empirical Diversification Behavior

Both commercial fishers' diversification decisions and network topology have changed over time—regressing yearly regional network-level metrics on observed diversification decisions shows that shifts in fishing behavior

are reflected in fishery network topology (Table 1). While the two measures of diversification (mean fisheries per vessel and sum of unique fishing strategies) describe similar behavioral responses, they are correlated differently with network structure.

Holding the number of strategies constant, an increase in the average number of fisheries per vessel by 1% is associated with a network of 26.11 fewer fishery nodes (for reference, annual regional networks range in number of nodes from 10-58 fishery nodes, Table SI.1). Comparing specifications with and without regional Fixed-effects highlights that more diversified networks in California are found in regions with fewer fisheries and within a region, a change in vessel diversification unaccompanied by a similar change in fleet strategies has little effect on network size (Table 1, specifications 1-4). Regardless of how diversified *individual* agents are, the heterogeneity in behavior in the system is the primary indicator of network structure in both number of nodes and number of edges. More unique strategies in the fleet is persistently correlated with a larger network with more connections: 20.59 more nodes and 77.04 more edges.

Dependent Variables:	Fishery Nodes		Edges		Mean Weight		Modularity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean Fisheries / Vessel	-26.11***	-9.503	-11.56	13.68	7.637***	6.344***	-0.8233***	-0.1265
(log)	(6.420)	(6.183)	(23.20)	(25.67)	(1.128)	(0.9781)	(0.1744)	(0.0938)
# Unique Strategies	20.59***	18.42***	77.04***	77.97***	-0.4896*	-0.7719**	0.1134***	-0.0098
(log)	(1.592)	(2.082)	(5.754)	(8.643)	(0.2798)	(0.3293)	(0.0432)	(0.0316)
Region Fixed-effects		Yes		Yes		Yes		Yes
Observations	154	154	154	154	154	154	154	154
R^2	0.616	0.761	0.723	0.772	0.323	0.659	0.139	0.833
Within R^2		0.507		0.606		0.293		0.042

*IID standard-errors in parentheses. ***: 0.01, **: 0.05, *: 0.1*

Table 1: Estimated OLS results in which I regress annual (t) network outcomes on observed diversification decisions by region (r), $\mathbf{NetworkMeasure}_{rt} = \beta_0 + \beta_1 \mathbf{log}(\mathbf{MeanDiversification})_{rt} + \beta_2 \mathbf{log}(\mathbf{UniqueStrategies})_{rt} + \gamma_r + \varepsilon_{rt}$. The two measures of diversification, while similar, are correlated differently with network topology.

When regional vessels on average choose to participate in an additional fishery, the network edges are more strongly weighted and the network as a whole is less modular (Table 1, specifications 5-8). Which is to say holding the configuration of collective behavior constant, increases in fishing diversification brings greater connectivity within a network. The specification with Fixed-effects shows that vessels in more diversified regions exhibit more adaptive behavior: not only do spillover expectations increase between pairwise fisheries, but also otherwise distinct fishery modules become linked. An increase in edge weights of 7.67 would mean that the average pair of fisheries shares that many additional vessels (for reference, San Diego averaged the smallest fleet over the study period of 45 vessels; Bodega the largest with 120, Table SI.1). In contrast, changes in the number of unique strategies—while associated with a broader network with more edges—accompany slightly lower edge weights and better delineated modules.

The empirical results reveal that average vessel diversification and the number of unique fleet strategies have distinct associations with network structure. While shifting species ranges, fishery closures, and fishery policies transform fishing incentives, it is uncertain how the different diversification responses mediate the shocks' impacts on the networks and how these effects depend on the existing system configuration. The structural simulation framework allows for vessel decisions and network topology to be jointly determined in order to better understand the mechanisms linking climate shocks, fishing behavior, and network responses and, more generally, how network measures reflect adaptive behavior.

Simulated Diversification Responses to Input Parameters

Simulated vessels' can respond to higher fishing and switching costs by (1) choosing to participate in fewer fisheries or (2) choosing a more common fishery strategy. Fishing diversification responds to input costs monotonically: as costs increase, the fleet reduces their diversification. Fewer vessels choose to participate in more than one fishery, vessels on average participate in fewer fisheries, and collectively the fleet employs fewer unique strategies (Table 2).

Dependent Variables:	# Unique Strategies (1)	Mean Fisheries / Vessel (all vessels) (2)	Mean Fisheries / Vessel (div. vessels) (3)	# Diversified Vessels (4)	# Fishery Nodes (5)	# Edges (6)
Switching Costs	-21.36***	-0.4732***	-0.3794***	-56.18***	-5.361***	-28.68***
	(1.470)	(0.0483)	(0.0289)	(4.012)	(0.2101)	(2.042)
Fishing Costs	-3.441**	-0.1099**	-0.1565***	-10.91***	-0.7417***	-5.957***
	(1.470)	(0.0483)	(0.0289)	(4.012)	(0.2101)	(2.042)
Observations s	100	100	100	100	100	100
R^2	0.693	0.513	0.681	0.680	0.873	0.682

*IID standard-errors in parentheses. ***: 0.01, **: 0.05, *: 0.1*

Table 2: Regressing simulated input scalars (z-scores of draws $\sim \mathcal{U}(0, 5)$) on diversification outcomes reveals that rising costs cause vessels to choose to participate in fewer fisheries and to use a more common strategy.

When the switching cost scaling parameter β increases by one standard deviation, the mean diversification level in the fleet decreases by 0.48 fisheries, there are 56.18 (19%, Table SI.2) fewer diversified vessels, and they collectively employ 21.36 fewer strategies. The reduction in unique strategies suggests that under costlier conditions, not only will vessels be less diverse, but as a fleet their set of strategies reduces to few dominant strategies. Increased fleet-wide costs restrict the set of profitable fisheries. One option for vessels is to truncate their strategy, in turn reducing the mean fisheries per vessel. The other option is to shift their strategy, switching from the fisheries that are no longer profitable to those that remain profitable in the higher cost setting.

Aggregate diversification patterns respond less to fishing cost changes than to switching cost changes. When the fishing cost parameter α increases by one standard deviation, only 2.71 (0.009%) fewer vessels choose to diversify and mean diversification decreases by 0.021 fisheries per vessel. While vessels respond to higher labor costs by becoming less diversified, as a fleet they may collectively employ the same number of strategies. The sensitivity of vessel diversification behavior to switching costs correlates with a similar sensitivity of the network structure. When fewer vessels diversify, there are fewer vessels available to connect fishery nodes: both the number of fishery nodes and edges in the network connected component decrease in response to switching costs.

Network Sensitivity to Input Parameters

The changes in diversification drive changes in the network structure. As inputs change, so too do the networks as vessels change their effort and diversification and the set of strategies change. In simulations with higher input fishing and switching cost parameters, the networks have fewer fisheries, with fewer edges and weaker edge weights than in baseline simulations. The decrease in edges and edge weights suggests that there is less capacity for spillovers: a perturbation at a given fishery would be expected to impact fewer fisheries, and any impact would be smaller.

Figure 2 demonstrates the rise in both fishing and switching costs from the left to right networks, along with the corresponding decreases in the fishery nodes and edges observed in the network. As vessels throughout a simulation iteration are individually and collectively less diversified, the largest connected

component contains fewer fisheries, with fewer and weaker observed instances of co-participation across fishery pairs. The networks appear successively smaller and more sparse. The shrinking network reflects the decrease in the number of strategies: with fewer strategies there are fewer overlaps in strategy sets and fewer fisheries found in the largest collection of interconnected sets. Fewer fisheries per vessel implies fewer and lower weighted edges. The mean diversification reflects fewer diversified vessels linking fishery nodes, and fewer vessels to use each strategy. Further, the decrease in mean diversification implies fewer fisheries per strategy, reducing the edges per strategy.

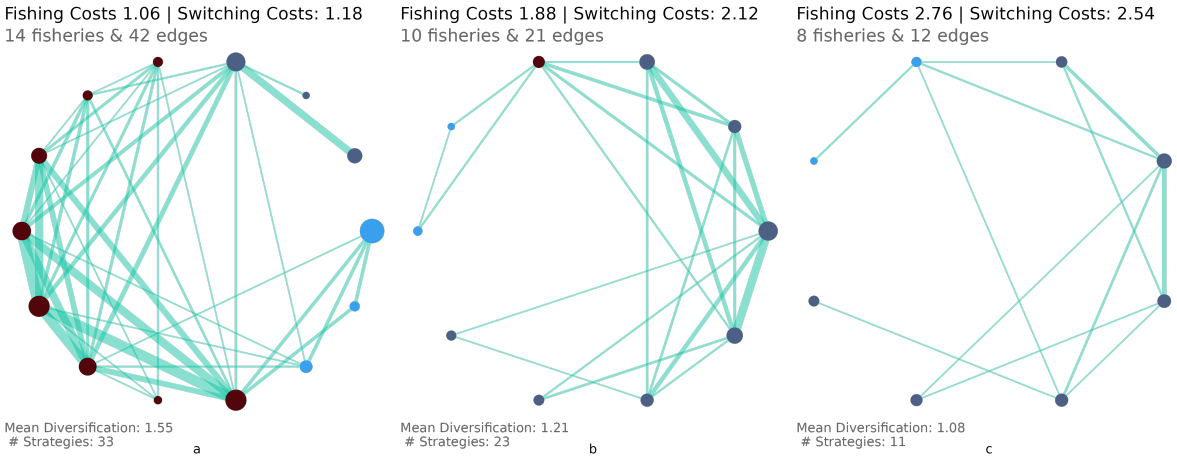

Figure 2: Examples of simulated fishery networks from 3 iterations, arranged by fishing costs. Diversification and # strategies decreases with costs, as does mean edge weight and the number of nodes and edges. Node colors indicate fishery clusters. **A** A network in a low cost setting. Vessels average 1.55 fisheries, and collectively use 33 unique strategies. This behavior creates a visually dense network, in which 14 fisheries are connected with 42 edges, weighted 6.17 vessels on average. In contrast, panels **B** and **C** depict networks in increasingly higher cost settings. Vessels diversify less, participating in fewer fisheries and as a fleet employing fewer unique strategies. In doing so, they connect fewer fisheries with fewer edges of lower weights.

Relating Diversification and Network Measures

Vessels respond to higher costs by choosing to participate in fewer fisheries or to use a more common strategy. The two responses—while highly correlated—can change network topology differently. As illustrated in Figure 3, increases in diversification of either kind are positively correlated with larger and more well connected networks. However, when only the number of strategies increases, the network mean weight is observed to decrease. While there are more edges in each simulation network, many of the new edges are connected by few co-participating vessels. Visually, going from left to right in figure 2, there is more blank space in the network, showing the comparatively narrower width of edges present and the absence of edges relative to the new network size. Both types of diversification decrease connectance as the increase in nodes and possible edges from the introduction of new strategies outpaces the observed co-participation. However, while connectance decreases by 13% and 11% when vessels try strategies new to the fleet (left to right), connectance decreases by only 3% and 1% when vessels participate in more fisheries (top to bottom).

Diversification responds to increased costs intuitively, but the nature of the responses can vary. Network measures bring insights otherwise unavailable. In the case of the top two networks, adding more strategies makes the network less modular. The top left network has two distinct modules, well connected with no nodes connected to fewer than two other nodes. The increase in strategies found in the network on the right brings more fishery nodes and edges into the primary connected component. The edges are concentrated, reinforcing connections with the large module while eroding the second module. Contrast this to the change in the bottom networks, where the increase in strategies increases modularity: the new nodes and edges strengthen

the comparative connectivity within the two modules as the large one (blue) gets more interconnected and the smaller one (purple) grows in number of nodes. These two different kinds of growth (or conversely, shrinkage) demonstrate that networks can experience changes in decision making conditions that, while having similar impacts on diversification decisions, vary in their impacts on the network topology.

The direct effect of switching costs on mean edge weight and modularity is non-linear and distinct from the indirect effects mediated through diversification. As switching costs increase (Figure 4a), both measures of diversification (fisheries / vessel and # unique strategies) decrease. When holding diversification constant, increases in switching costs can increase mean edge weight as mediated through the number of fishery nodes: fewer fishery nodes in a system with the same level of diversification implies the remaining edges will be weighted more heavily. Holding fishery nodes constant, the impact of switching costs on mean weight and modularity mediated through changes in mean fisheries per vessel (< 0) is the opposite of that mediated through number of unique strategies (> 0). Figure 4b explores the mechanism of this dynamic, in which each green square is a group of vessels sharing the same unique strategy. The lines connecting each set of vessels to the fishery nodes in which they participate is weighted by the number of vessels using the group strategy.[3]

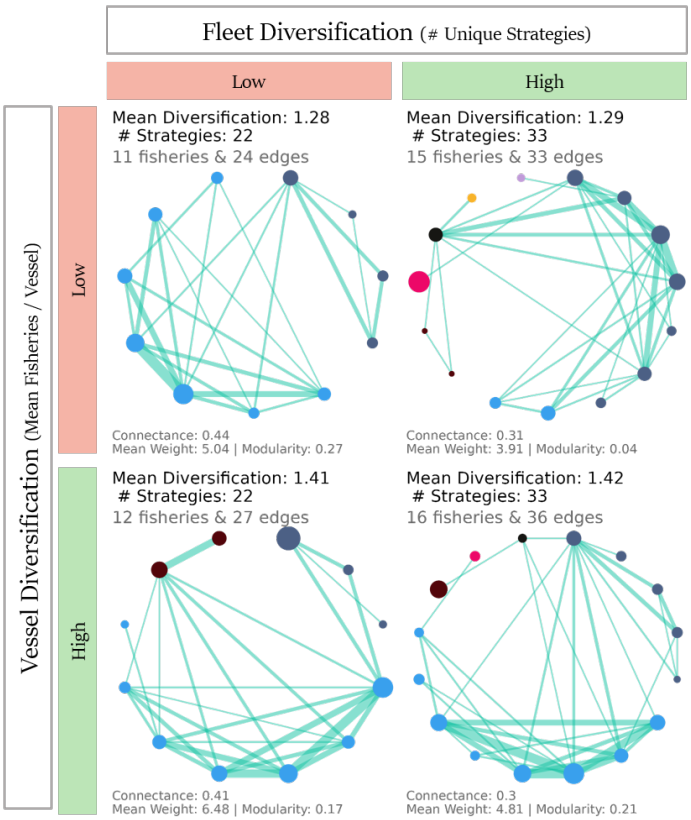

Figure 3: Examples of simulated fishery networks from 4 iterations, arranged by observed # fisheries \vessel (columns) and # unique strategies (rows). While mean edge weight and spillover expectation increases with fisheries / vessel (left to right), it decreases with the number of unique strategies (top to bottom). Node colors indicate fishery clusters.

Holding strategies constant, as rising switching costs decrease mean diversification mean edge weight and modularity decrease. Fewer vessels contribute to edge weights and the reduction in diversification weakens within-module connectivity. For example, consider the change between networks a and b in Figure 4b. The increased costs cause some vessels in groups 1, 5, and 7 to participate in only one fishery: they no longer contribute to edge weights. Fewer vessels in groups 1, 5, and 7 in network b yields lower within-module connectivity relative to across-module connectivity and modularity decreases relative to network a. Contrast this to the decrease in the number of unique strategies—holding constant fisheries per vessel—which is correlated with increases in mean edge weight and modularity. In Figure 4b.c, the number of unique strategies collapses from eight (as in network a) to four. For instance, the vessels in group 2 cease to participate in fishery d and their new strategy is that of group 1. Network c has

[3]Note that this is a depiction of the underlying *bipartite* network of both fishery and vessel nodes. The network in this paper is a single-mode projection of the underlying network into fishery-fishery space, as demonstrated in Figure 1. For example, the edge between fisheries a and b (the first two blue circles) takes the weight of the number of vessels belonging to vessel groups 1 and 2 (the first two green squares).

fewer edges between fishery nodes compared to network a. The lost edges had connected the two modules and were of low weight—network c has both higher mean edge weight and modularity than network a.

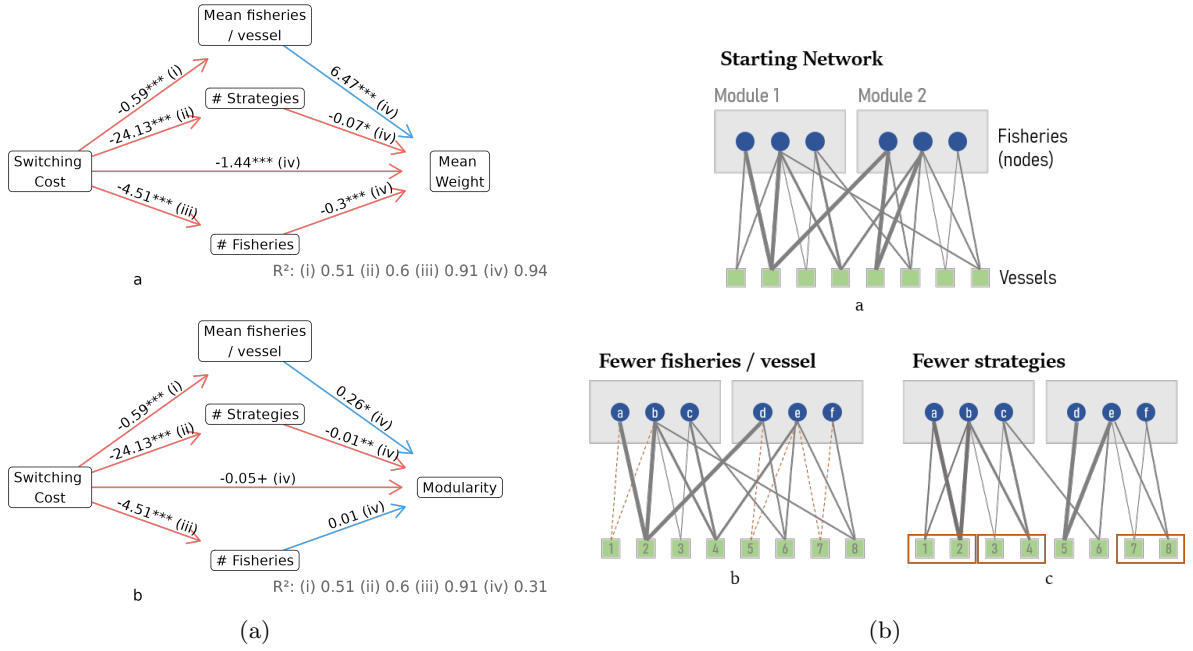

Figure 4: **(a)** Directed acyclic graphs depicting the direct and indirect effects of switching costs on network topology. For regressions (i, ii, iii), I estimate the correlation between fisheries / vessel, # strategies, and # fishery nodes and switching cost, respectively. For regression (iv) I estimate $Y_i = \beta_0 + \beta_1 \textbf{SwitchingCosts} + \beta_2 \textbf{MeanDiversification} + \beta_3 \textbf{UniqueStrategies} + \beta_4 \#\textbf{FisheryNodes} + \varepsilon_i$ for $Y_=$ mean edge weight (a) and modularity (b). Coefficient estimates are on the edge between them, colored by their sign, with R^2 below. **(b)** An example of how increased switching costs can alter a network topology (b.a) when mediated through fewer fisheries per vessel (b.b) or fewer strategies (b.c). The green squares are vessel groups that use a common strategy, as indicated by lines to the blue fishery circles weighted by the number of vessels in the group. In scenario (b.b), there are fewer vessels in groups 1,5, and 7 (dashed red lines). Mean fisheries / vessel, mean edge weight, and modularity decrease; the lost edge weight had reinforced modules. In scenario (b.c), the vessels in group 2, 4, and 8 adopt the strategies of groups 1, 3, and 7, respectively. Modularity and mean edge weight increases.

The indirect effects of switching costs are statistically insignificant when we consider the parabolic relationship between modularity and switching costs (Figure SI.2). Figure 5e shows modularity increases for the switching cost domain $[0, 3)$ ($n \gtrsim 10$, $\hat{\rho} = 0.092$) and decreasing along $[3, 5]$ ($n \lesssim 10$, $\hat{\rho} = -0.099$). One way to interpret the nonlinearities in network responses is through the impact of switching costs on network structures—the reduction in diversification reduces both observed fishery node and edge counts (Figure 5a, 5b). However, the monotonic decreases in nodes and edges result in non-monotonic responses in connectance. Connectance decreases until approximately the same turning point as modularity (Figure 5c)— $\beta \approx 3, n \approx 10$— at which point the decline in number of fishery nodes relatively outpaces that of edges in response to switching costs. Applying the results in Gilbert (2009), when switching costs are low, a marginal increase in switching costs reduces fishing diversification at comparatively well-connected nodes (adjacent to many edges)—those nodes become disconnected from the network and network connectance decreases. At higher switching costs, the disconnected nodes are relatively less connected (adjacent to few edges) and connectance increases.

When increased costs decrease diversification such that well-connected nodes exit the network, we observe the changes in network measures we have come to expect from the prior results: the networks become less connected, more modular and with weaker edges (Figure 5). However, when increased costs alter system

dynamics such that poorly-connected nodes exit the network, we observe unexpected changes in the networks as they become less modular, denser, and less fragmented. We observe the former topological changes in larger networks and the latter in smaller networks: the same exogenous shock can have opposite effects on network topology depending on network size. For example, it is possible that a node that is well-connected in a larger network (and whose exit decreases connectance) may be relatively poorly-connected in a smaller network (and its exit would increase connectance). The dynamics of a large network can define a regime in which small changes to decision-making conditions bring about small and predictable changes to network topology—shrinking the network without reconfiguring fishery node locations. A large change in costs can cause a switch to a small network regime defined by new fishery node locations, bringing about a large and unpredictable change in network topology. The difference between within- and across-network size effects suggests that network topology is easiest to interpret in response to small changes in decision making conditions. The interpretation of network measures depends on network structure and underlying decision-making conditions and is therefore regime-dependent.

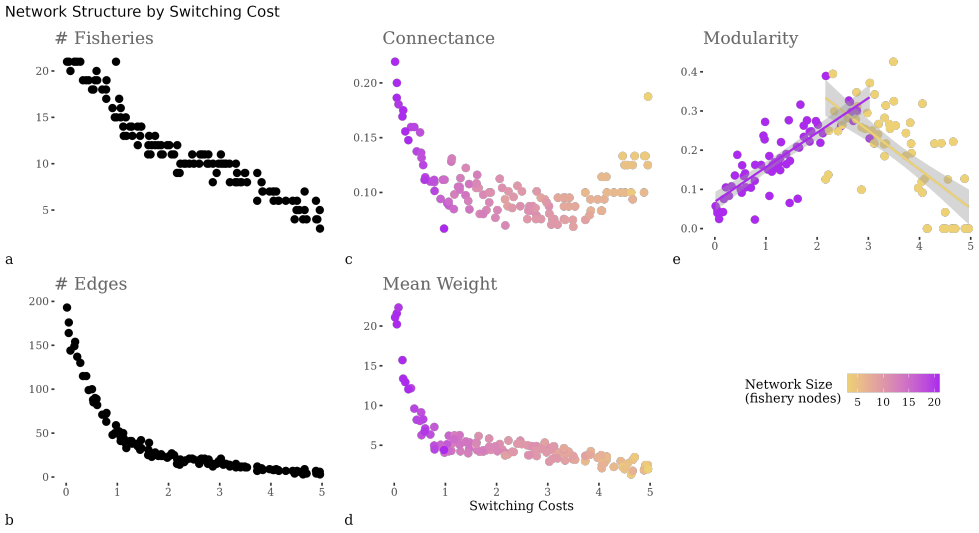

Figure 5: **(a, b)** Scatter plots of # fishery nodes and # edges, both decreasing with switching costs. **(c)** Connectance decreases until the decrease in fishery nodes outpaces that of edges. **(d, e)** Scatter plots of network outcomes, depicting mean weight decreasing at a decreasing rate, and the concave parabolic response of modularity. Colors aid in pairing network measure relationship to network size, showing the shifts occurring at ≈ 10 fishery nodes. Fishing costs are held constant and $SC = 1$ is the switching cost level calibrated to CA fishing.

It is important to note that one cause of regime-dependent interpretation may be due to the nature of modularity, which is 0 in networks of one module, regardless of edge weights. Networks with fewer than four nodes (as found in Fisher et al. (2021) and Fuller et al. (2017)) necessarily have modularity equal to zero, creating a censored panel that biases estimates. This critical feature of modularity is overlooked in the fishery economics literature and implies that modularity is a network measure that is most consistently interpreted when there are two or more distinct modules of two or more nodes.

Regime-Dependent Interpretation of Network Measures

I extend the study of marine system regimes to network topology of commercial fishing systems, finding that the relationships between individual vessels' fishing behavior and collective system structure vary across both time and space. Using both empirically observed and simulated California commercial fishing decisions, I show that network measure interpretation is regime-dependent. Similar to the prior section, I differentiate

regimes by the patterns in the connection between fishing behavior and network interpretation. I consider each direction of correlation to represent a regime, within which a policy-maker could consistently interpret the impact of fishing diversification on system resilience.

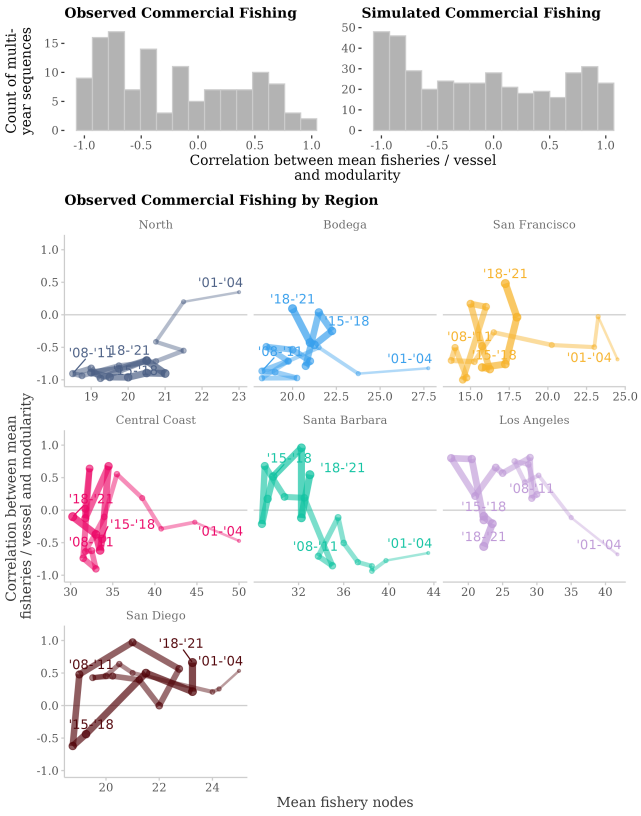

Figure 6: Each observation is a 4-year sequence in the empirical or simulated setting. **Top:** Side by side histograms of correlations between diversification and modularity in the empirical (left) and simulated (right) settings. Both show bi-modality, reflecting that the same change in fishing behavior can have opposite effects on topology. **Bottom:** Correlations (y-axis) by network size (x-axis) per region over time in empirical setting. Thickness of points and lines increase with year. Colors by region. California regional networks are observed to belong to different network-behavior regimes, and pass through different regimes over time.

I focus on modularity, which I observe in the simulated fishing data to be negatively correlated with diversification in some cost settings, and positively correlated with diversification in others (Figure 5). I compare this finding to the empirical setting of California commercial fishing, in which for each region I construct four-year sequences from 2000-2021, allowing me to test multi-year sequences to belong to either regimes. In the simulation, I bootstrap multi-year sequences, for which I subset simulation iterations by their switching and fishing costs and draw four iterations at random to represent four sequential years in a region. Both approaches are outcome agnostic: I do not impose priors on the trends of fishing diversification and modularity when delineating or constructing multi-year periods.

I observe a similar bimodal distribution in the correlation between diversification and modularity in the observed and simulated fishing data (Figure 6, top). However, within each region in the empirical setting I find a unimodal distribution, each with a unique policy implication. Unimodality within regions provides support for the existence of at least two regimes: one in which an increase in diversification could be expected to accompany an increase modularity and one in which it would accompany a decrease modularity. In the North, Bodega, and San Francisco regions, modularity is consistently negatively correlated with vessel diversification (Figure 6, bottom). The San Diego and Los Angeles regions belong to another regime, in which increases in diversification have been correlated with increases in modularity. Santa Barbara and Central Coast ports have been less consistent in regimes—in Santa Barbara there was an observable shift from the negative-correlation regime to the positive-correlation regime (Figure 6, bottom). The grouping of regions into regimes coincides with geographical position and known fishing behaviors. The northern regions are dependent on the salmon and Dungeness crab fisheries, and the southern regions are dependent on the squid fishery; the geographically centered regions oscillate between resembling their northern and southern counterparts.

At any given time, California regions are observed to belong to different regimes and some regions pass through different regimes over time. In the regime to which the Northern regions belong, decreases in vessel

diversification are associated with a reduction in modularity, such that future spillovers will be unconstrained to a given network module.[4] However in the regime to which the Southern regions belong, the *same behavioral response* brought about an *entirely different network response*—a topology that suggests a perturbation in one fishery would be contained to its module.

To understand the underlying dynamics differentiating regimes, I compare the empirical sequences to simulated bootstrapped sequences. Simulation iterations are identified by random draws of fishing and switching cost scalars. While this variation is far simpler than the sources of variation differentiating regimes in the empirical setting, the exercise offers some insight into how decision-making conditions can impact network-interpretation regimes. Similar to the empirical setting, the correlation between diversification and modularity has a distribution that is bimodal for all sequences and unimodal when subsetting sequences by input costs.

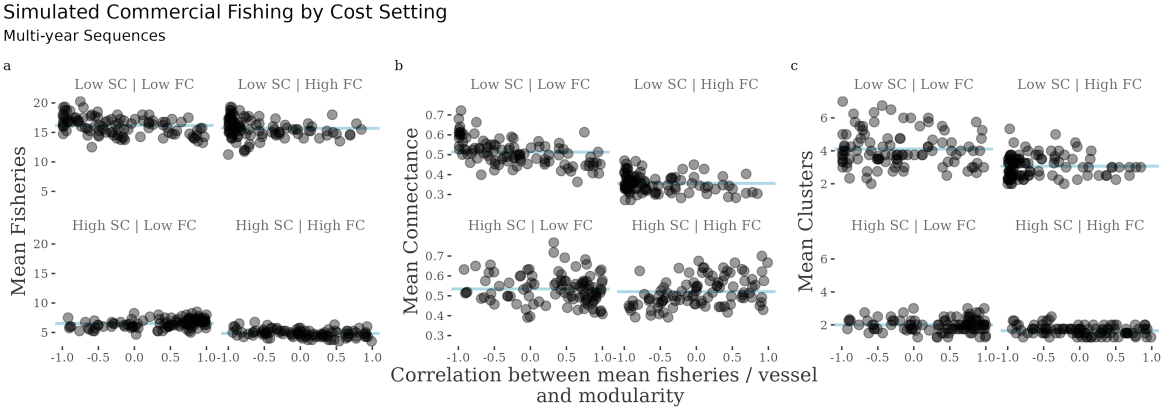

Figure 7: Each observation in each scatter-plot is a simulated multi-year sequence. X-axis is the correlation between modularity and diversification, and each plot is broken up by the cost setting: high and low switching and fishing costs (low switching costs in top row, low fishing costs in left column). Horizontal line shows mean for that setting. **A** Y-axis is mean network size in nodes across years. Low switching costs have bigger networks. **B** Y-axis is mean connectance: the cost setting with the most reliably negative correlation between modularity and diversification is the one with the lowest connectance. **C** Y-axis is mean # modules, showing the possible truncation in modularity measure found in high switching costs settings.

I subset the simulated sequences into four groups based on combinations of high and low switching and fishing costs. In both low switching cost settings, more diversification is correlated with larger networks and lower modularity (Figure 7a). Vessels' decision to participate in more fisheries strengthens edges between modules when it is cheaper to switch. This trend is strongest when fishing costs are higher and connectance is lower (Figure 7b), suggesting that modularity is more sensitive to decision-making conditions in networks with fewer relative edges. When vessels diversify more in less connected networks, the additional edge weights are more likely to connect distinct modules; whereas when they diversify in more connected networks, the additional edge weights are comparatively more likely to reinforce existing modules. In terms of resilience, in settings of higher fishing costs, more diversification can increase the potential for few strong spillovers, while in settings of lower fishing costs, more diversification can increase the potential for more fisheries and vessels to experience spillovers.

In the two high switching cost settings, increases in diversification are more positively correlated with modularity than in the low switching cost settings. This may be due to the limited range of modularity values that arise in small networks (explained above). When changes in behavior patterns cause a reduction in fishery nodes beyond a certain threshold, it is more difficult to draw inferences from trends observed

[4] figure to come

between the new smaller networks. Increased diversification in these small networks is likely to create more modularity as vessel diversification creates additional modules and modularity greater than 0 (Figure 7c). In high fishing cost and high switching costs, the networks may be so small that additional diversification fails to create a second module, leading to ambiguous relationships between diversification and modularity. This reinforces the regime-dependence in interpreting modularity: not only does connectance change how modularity relates to diversification, but some regimes may lack the network size for network measures to respond consistently to changes in fishing behavior.

Discussion

Network measures provide insight into the climate sensitivity of complex systems (Mahon et al., 2008; Montoya et al., 2006; Battiston et al., 2020; Grilli et al., 2017), yet interpretation in commercial fishery systems has been, until now, hypothetical. As climate change increases the frequency and magnitude of stresses to ocean ecosystems, it is increasingly critical to understand the resilience of natural resource-dependent communities. Using structurally simulated fishing decisions alongside empirically observed outcomes, I provide interpretations of network measures that can be used to assess system vulnerability. I quantify the sensitivity of fishing behavior to changes in fish population dynamics, marine heatwaves, and policies. Further, I demonstrate the nuances in the correlations between adaptive fishing decisions and network topology. In doing so, I generate testable hypotheses on the relationships between network measures and responses to system stress. For example, Scheffer et al. (2012) find that more connectance and edge weights can indicate system resistance to small changes but sudden systemic transitions to larger changes. I find that increasing vessel and fleet diversification are both correlated with decreasing connectance and edge weights. I hypothesize that fishing diversification is a reliable predictor of widespread vessel exits from the commercial fishing industry in response to a Dungeness Crab seasonal closure.

By simulating commercial fishing decisions in California, I show that individual fishers' responses to climate and policy shocks can change the susceptibility of the system to future climate and policy shocks. A policy that reduces access costs for a fishery in the region will have a different effect on resilience than one that makes a new fishery available or otherwise decreases access costs. In the former, vessels mirror the most diversified vessels' decisions and a shock in a given fishery is likely to have large spillover effects on few fisheries (higher edge weights in the same sized network). In the latter, vessels branch out, and more fisheries are likely to experience smaller spillover effects (lower edge weights in a less connected and bigger network).

I develop new insight to the relationship between modularity and resilience. First, I find that while increased *individual* diversification increases modularity, heterogeneity in *fleet* strategies decrease modularity (Figure 4a). Second, I point out the inverse relationship between modularity and connectance (Figure 5). Under low cost settings (e.g., open access conditions), participation decisions that increase diversification will decrease modularity; however, in higher cost settings (e.g., restricted access conditions, marine heat waves, fishery collapse), diversification will reinforce existing modules (Figure 7). Third, I condition my interpretations of modularity on network size. The network measure is informative for community resilience, but it requires multiple modules of more than 1 node in order to be interpreted consistently. This is frequently overlooked in the fishery economics literature that includes analysis of regional networks of fewer than 5 nodes (Fisher et al., 2021; Fuller et al., 2017).

Modularity is an uncertain indicator of resilience, as it can represent agents constrained in their options (Stoll et al., 2016) or buffered against unfavorable perturbations (Earn et al., 2000). Small changes in modularity can reflect different changes in diversification behavior depending on the state of the system. Diversification is an expensive adaptive behavior and as fishing conditions become costlier, we observe not

only a change in the affordability of diversification but also a system reconfiguration. While the core set of fisheries (Dungeness Crab and Salmon) remain constant, the loss of peripheral fisheries equates to a loss of redundancy in adaptive strategies (Gunderson and Pritchard, 2012). The reduced variety in system structures accompanying the change in topological patterns implies that the interpretation of modularity as an indicator of resilience is dependent on the state of the system. Further, changes in fishing access can increase the likelihood of the system to cross a threshold into a different regime (Walker et al., 2004; Salt and Walker, 2006). I demonstrate that in California, regional fleets are observed to belong to different regimes, and have passed through different regimes over time.

One limitation in this research is that my simulation models myopic decision-making: vessel operators choose fisheries based only on the expected revenue of the current week. This simplification may explain some of the variation between the outcomes in the simulated and empirical settings, given that commercial fishers are forward looking (i.e. to mitigate risk). Despite this limitation, I am able to use calibration and discrete choice dynamics to successfully generate outcomes that resemble historical commercial fishing in California.

I explore network structure using two network measures: mean edge weight and modularity. Future work can build upon this by exploring the microfoundations of other network measures, e.g. density, fragmentation, or nestedness. Additionally, the commercial fishing industry in California is an example of a setting with known central fishery-nodes: fishing behavior is highly responsive to climate and policy shocks to the Dungeness Crab and Salmon fisheries (Fisher et al., 2021; Free et al., 2023). Network research in this setting would benefit from understanding the relationship between individual decisions and node-level measures including closeness, betweenness, local density, and fragmentation centrality.

In this paper, I compare simulation iterations to draw conclusions about how network measures reflect decision-making conditions. I also provide interpretations that draw upon existing theories of network measures. However, the interpretations are limited by the uncertain implications of spillovers. While a well connected system indicates that the fishing vessels have adaptive behaviors available to them in the case of exogenous shocks, the fisheries connected to the shock experience a larger spillover (Valdovinos et al., 2016). Further, a system's resilience to small exogenous shocks can vary from its resilience to a large shocks (Scheffer et al., 2012). How should policy makers weigh the tradeoffs between adaptive behavior as dampening disruptions or proliferating spillovers given the inherent uncertainty of climate shocks? What are the implications for diversification policy—such as flexible fishing permits and fishery access—in sustaining both fish stocks and the fishing community over time? Extensions of this research can apply these findings alongside existing network theory in order to better predict future climate and policy shocks.

This research draws connections between individual-level commercial fishing decisions and adaptive behaviors and fleet-level decision-making conditions and system topology. The model in this paper does not explicitly consider fishing employment, alternative employment, or subsequent regional effects. For instance, vessel operators can choose to cope with external shocks without changing their fishery participation through reducing their labor demand or supplementing their fishing employment (Fisher et al., 2026). The impacts of these decisions on the fishing community can vary based on local characteristics such as the community's reliance on the commercial fishing industry (Jardine et al., 2020). Future work can pair fishing network analyses with regional economic and employment data in order to account for the full range of adaptive decisions and feedback links. This will provide insight for resilience that considers not only the continued income and participation of vessels in the industry, but also community well-being more broadly.

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Supplemental Information

Methods

California Port and Region Map

Figure SI.1: California fishing port names, locations, and the regions used. Fishing vessels have a home region, and choose to participate in region-fisheries (ex: Bodega Salmon distinct from San Francisco Salmon).

Fishing Costs

I use the estimated expected revenue and the observed empirical fishing behavior to optimize an alternative specific cost that reproduces the observed fishing shares in California. Fishing cost constants for each vessel class and region-fishery are calibrated to the empirical setting with a contraction mapping, minimizing the sum squared error between the simulated and empirical share of vessel weeks in which all vessels of each class participate in each region-fishery. I calibrate alternative-specific constants for the fishing costs of each home region and fishery-region combination.

In the fishery-region setting, a vessels' home region is the one in which they land the plurality of their catch. In order for the simulated behavior to reflect this assignment heuristic, I assign a travel cost for fishing regions away from a vessel's home region,

$$D_{r_i r_j}(R_{ij}, \psi) = \psi R_{ij} + 1.$$

ψ is a constant distant scalar for the simulation and R_{ij} is the ij^{th} element of the distance matrix R. In the distance matrix R, region row/columns are arranged by latitude, such that $R_{ii} = 0, R_{i,i_{+1}} = 1, ..., R_{i,i_{+x}} = x$.

Regardless of ψ, fishing costs scale proportionally to the number of regions between the home port region and the fishery region. In the base series of simulations $\psi = .3$; in more stochastic simulation series $\psi \sim \text{Uniform}(0, 10)$ to describe settings in which travel is more costly, even prohibitively so.

R	No.	Bd.	SF	CC	SB	LA	SD
North	0	1	2	3	4	5	6
Bodega	1	0	1	2	3	4	5
San Francisco	2	1	0	1	2	3	4
Central Coast	3	2	1	0	1	2	3
Santa Barbara	4	3	2	1	0	1	2
Los Angeles	5	4	3	2	1	0	1
San Diego	6	5	4	3	2	1	0

Switching Costs

Using nonlinear optimization, I optimize switching cost constants for each pairwise combination of regional fisheries to minimize error in joint fishery co-participation: the number of vessels participating in all pairwise combinations of regional fisheries.

Stock Effects

A stock effect for each fishery limits the number of vessel weeks available for that fishery. If simulation fishing outpaces empirical landings in weeks $[0, w-1]$, simulated expected revenue faced by vessels in week w are scaled by the ratio of simulated vessel-weeks (sum of weeks chosen by all vessels to participate in a given fishery) to empirical vessel-weeks in weeks in $[0, w-1]$. Each element of the time-variant vector, $\mathbf{T_{f \times 1}}$, scales the expected revenue for all vessel classes for fishery f in week w. Following the decisions of week w, $\mathbf{T}$ is updated to include the fishing behavior in weeks $[0, w-1]$. At the end of each year of the simulation stock effects reset to $\mathbf{T} = 1$.

Directed Acyclic Graph, Polynomial Degree 2

Summary Statistics

Fishing diversification and networks in California regions, 2001-2021

Variable	Min	Median	Mean	Max	SD
Mean Diversification	1.237	1.810	1.816	2.313	0.206
# Strategies	13.000	46.000	49.929	135.000	23.859
# Fishery Nodes	10.000	24.000	26.325	58.000	9.602
# Edges	15.000	65.500	76.416	233.000	40.829
Mean Edge Weight	1.417	3.048	3.309	7.702	1.271
Modularity	0.008	0.225	0.267	0.625	0.174

Table SI.1: Summary statistics by region (n = 7) and year (n = 22), 154 observations

Fishing diversification and networks in 100 simulated years

Variable	Min	Median	Mean	Max	SD
Mean Diversification	1.01	1.121	1.412	4.644	0.682
# Strategies	2.00	11.000	23.350	122.000	26.105
# Diversified Vessel Links	3.00	24.500	55.920	283.000	69.785
# Fishery Nodes	3.00	8.000	10.260	21.000	5.813
# Edges	2.00	12.500	29.780	163.000	35.658
Mean Edge Weight	1.00	3.335	4.062	18.239	3.087
Modularity	0.00	0.159	0.163	0.455	0.134

Table SI.2: Summary statistics by iteration, 100 observations, for draws of input scalars for switching costs and fishing costs $\sim \mathcal{U}(0, 5)$

Figures

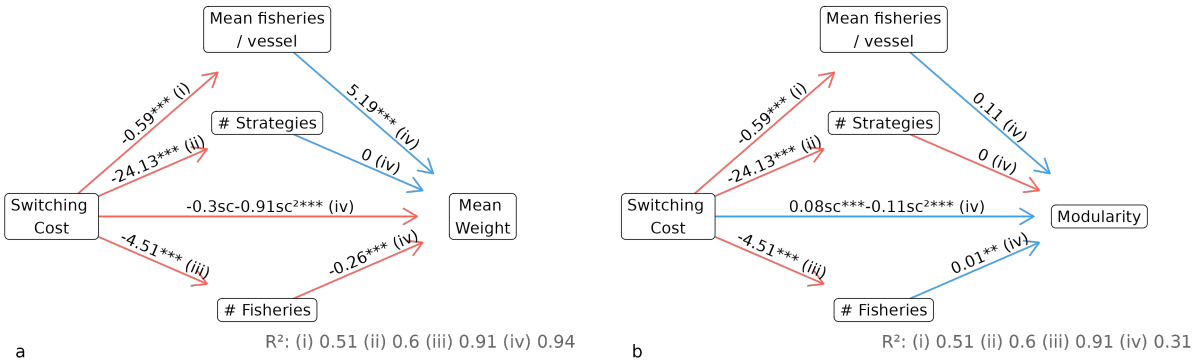

Figure SI.2: Directed acyclic graphs depicting the direct and indirect effects of switching costs on network topology. For regressions (i, ii, iii), I estimate the correlation between fisheries / vessel, # strategies, and # fishery nodes and switching cost, respectively. For regression (iv) I estimate $Y_i = \beta_0 + \beta_1 \mathbf{SwitchingCosts} + \beta_2 \mathbf{SwitchingCosts}^2 + \beta_3 \mathbf{MeanDiversification} + \beta_4 \mathbf{UniqueStrategies} + \beta_5 \mathbf{\#FisheryNodes} + \varepsilon_i$ for $Y_=$ mean edge weight (a) and modularity (b). Coefficient estimates are on the edge between them, colored by their sign, with R^2 below.